Wind forcing calibration and wave hindcast comparison using multiple reanalysis and merged satellite wind datasets

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Abstract :

Wave hindcasts are tools to study climate and are regularly used in offshore and coastal engineering applications. The growing number of wind datasets and reanalysis products create more opportunity for generating wave hindcasts. Each wind dataset or reanalysis product has different resolution, model implementation, and assimilation scheme and if the wave model implementation is not calibrated to the input wind field the resulting wave field can have large biases solely due to the wind. In this work, we calibrate the wind to wave growth parameter within the spectral wave model WAVEWATCH III for 10 reanalysis datasets and 2 datasets composed of merged satellite observations. The calibration is performed globally by minimizing the differences between altimeter wave height observations and the model output for the year of 2001. We place special emphasis on ensuring the largest sea states are well captured and are not underestimated because of the important engineering applications of these data. After the calibration we compare the datasets and find each product reproduces the average sea states similarly, but high sea states have large discrepancies. We demonstrate that the space-time distribution of the extreme waves are very different even after calibration. We summarize by providing recommendations of the most accurate wind datasets to generate wave hindcasts.

Highlights

► Wave hindcast errors can be reduced by proper calibration of the wind input. ► The wind-to-wave growth parameter is calibrated for 12 wind datasets using altimeters. ► After calibration the hindcasts are similar for Hs P50 but deviate for the Hs maximum. ► It is demonstrated that strong storms have large differences in the wave hindcasts. ► Recommendations of the better wind forcing products are summarized.

Keywords : Wave hindcast, WAVEWATCH III, Wave climate, COWCLIP, Extreme waves, Reanalysis inter-comparison

1. Introduction

Understanding the wave climate is essential to understanding integrated ocean-atmosphere-wave interactions and mitigating damages caused by ocean surface waves. The design of structures in offshore and coastal regions is still largely based on data generated from wave hindcasts. This is due to the fact that they have high time and space resolution, are of high fidelity, and some are openly available (e.g. Rascle & Ardhuin, 2013; Chawla et al., 2013; Perez et al., 2017). In remote areas with limited in-situ and remote sensing observations, wave hindcasts are an attractive option to understand the wave climate variability (Stopa et al., 2016b; Thomson et al., 2016). There are uncertainties in the input wind fields and these impact the wave field. For example the noted overestimation of the wind speeds in the Southern Ocean before 1994 creates distinct positive biases in the wave field (Chawla et al., 2013; Rascle & Ardhuin, 2013; Stopa & Cheung, 2014). Wave hindcasts are typically generated using reanalysis datasets because they are evenly spaced in time and have high resolution. There have been many successful implementations of reanalysis-driven wave hindcasts (e.g. Cox & Swail, 2001; Caires & Sterl, 2005; Chawla et al., 2013; Rascle & Ardhuin, 2013; Perez et al., 2017)

There are a growing number of accurate wind products, creating more opportunity for generating wave hindcasts. Reanalysis assimilates observations into models, which sometimes consist of atmospheric, oceanic, land, and ice models, and generate evenly distributed global data. The first notable release of a comprehensive reanalysis dataset started with the National Center for Environmental Prediction (NCEP) reanalysis 1 (R1) (Kalnay et al., 1996). The European Center for Medium-Range Weather Forecasts (ECMWF) 15-year and 40-year reanalyses (ERA15; ERA40) (Uppala et al., 2005) and the Japanese Meteorological Agency's (JMA) 25-year reanalysis (JRA25) Onogi et al. (2007) followed suit with improvements. These efforts established best practices to collect, manage, and archive observations that are the backbone of the reanalysis products (Kistler et al., 2001). Now most weather centers have released updated and improved reanalysis versions: the NCEP the climate forecast system (CFSR) 1979-present (version 1 & 2) (Saha et al., 2010, 2014), the ECMWF ERA-Interim (ERA-Interim) 1979-present (Dee et al., 2011), the JMA 55-year (JRA55) 1958-present (Kobayashi et al., 2015), and the NASA Modern Era Retrospective-Analysis for Research and Applications v2 (MERRA) (Gelaro et al., 2017). Many of these datasets start in 1979 with the modern satellite era or when global radiosonde observations were established in 1958. In addition, there are reanalysis datasets that are constrained by atmospheric pressure observations to recreate

the entire 20th century such as the Cooperative Institute for Research in Environmental Sciences (CIRES) R20C (Compo et al., 2011) and the ECMWF ERA20C (Stickler et al., 2014). With the large amount of satellite wind observations from scatterometers and radiometers collected in the last 25 years there have been efforts to create merged and gridded products at regular time intervals (Atlas et al., 2011; Bentamy et al., 2016). As improvements to models, computing power increases, and better quality satellite observations become available it is expected that there will be continued efforts to generate reanalysis products every 5 to 10 years. Therefore there are many options to generate wave hindcasts and there need to be continual efforts to assess these products and their suitability to generate wave hindcasts (e.g. Caires et al., 2004; Stopa & Cheung, 2014).

Each wind dataset has different space-time resolution and the reanalysis datasets have different physical parameterizations, assimilation schemes, and assimilate different observations. All of these aspects change the characteristics of the surface wind field and when used to force a model will generate different wave fields. To introduce this idea, probability density functions (PDF) and quantile-quantile (QQ) plots are given in Figure 1 for the near surface wind speed (U_{10}) and the significant wave height (H_s) using several of the noted datasets. It is clear the U_{10} PDFs are different especially for high wind speeds ($>25 \text{ ms}^{-1}$). When using the same wave model implementation as in Figure 1(d,e,f), the generated wave field may not be consistent with wind forcing (e.g. R20C has no occurrences of $U_{10}>35 \text{ ms}^{-1}$ but has the largest sea states). The details of these plots will be discussed throughout the manuscript. Our first goal is to demonstrate that some biases in the wave field can be corrected by calibrating the wave model parameterization to the input wind field. Since the wave field is a smoothed version of the atmosphere, it is unclear how each of the differences in the forcing wind fields impact the wave field. Therefore, after calibration we compare the output wave fields to understand their differences. We place special emphasis on high sea states and provide recommendations of more accurate products to drive a wave hindcast.

The manuscript is organized as follows. In section 2, we describe the datasets, various reanalysis products, and wave model implementation used to create 1-year wave hindcasts. In section 3, we calibrate the wave model parameterization to the different wind datasets by comparing H_s to satellite altimeters for 2001. In section 4, we compare the 12 different calibrated one-year hindcasts to understand their behavior. Our recommendations and conclusions follow in section 5.

2. Datasets and model implementation

In this section the satellite and buoy observations, input wind fields, and model implementation are described.

2.1. Observations: merged altimeter dataset and moored buoys

The multi-platform altimeter product (abbreviated ALT herein), is quality controlled and calibrated between platforms and to moored buoys (Queffelec & Croize-Fillon, 2015). In this work we chose the year of 2001 for the analysis since all datasets overlapped during this period. In 2001, there are three altimeter platforms in orbit: European Remote Sensing 2 (ERS2) (1996-2011), TOPEX/Poseidon (TPX) (1993-2005), and Geosat Follow-on (GFO) (2000-2007). The multi-mission dataset is calibrated between platforms and we expect it to be a fairly homogeneous dataset. Since the 1-Hz altimeter measurements capture the instantaneous H_s it is an unfair comparison with the time-space averaged spectral wave model. Therefore we smooth the altimeter tracks for each platform within the wave model grid cell (0.5°) by taking a running mean of 5-points since each platform has a spatial footprint of 7-10 km. This dataset includes calibrated H_s and U10.

The National Data Buoy Center (NDBC) provides quality controlled wave data from their network. Our model implementation is at the global scale (55 km) so we chose buoys sufficiently far (>30 km) from the coastlines and located in deep water. In total there are 32 buoys that met our criteria and they grouped by regions: Hawaii (HAW): 51001, 51002, 51003, 51004; North Pacific (NoP): 46001, 46035, 46066; Northeast Pacific (NEP): 46002, 46005, 46006, 46011, 46012, 46014, 46022, 46023, 46025, 46028, 46042(2D), 46047, 46053, 46054, 46059, 46063; Gulf of Mexico (GoM): 42001(D), 42002(2D), 42003(2D), 42039(2D), 42040(2D); Northwest Atlantic (NWA): 41001, 41002, 41010, 44004. Only a select number of buoys have frequency-direction spectra (2D) available for comparison to the wave model as noted above. See Figure 7a for their locations, which are limited to the Northern Hemisphere near the United States coastlines. The frequency-direction wave spectra are created using the maximum entropy method (MEM) (Earle et al., 1999). The highest frequency adequately resolved by the buoys is 0.4 Hz. The model spectra are interpolated in time and space to match the buoy observations.

89 2.2. Forcing fields: wind and sea ice datasets

90 In the following subsections we will briefly describe the model forcing datasets used in this
91 study consisting of reanalysis and merged satellite products. Reanalysis assimilate various in-situ
92 and satellite observations using the same assimilation method and model settings. Some reanal-
93 ysis assimilate data in 4 dimensions (4D-VAR: x,y,z,t) (e.g. Dee et al., 2011), while others use 3
94 dimensions (3D-VAR) (x,y,z) for an initialization time step followed by a short forecast (typically
95 6 hours) (e.g. Saha et al., 2010). Most of the reanalysis datasets, with the exception of CFSR,
96 have prescribed sea ice concentrations from external sources such as radiometers and sea surface
97 temperatures (e.g. Dee et al., 2011; Hirahara et al., 2014). We summarize pertinent information
98 below and in Table 1. The readers are referred to each of the references for detail on each product.

99 2.2.1. NCEP R1

100 The NCEP R1 was the first long-term reanalysis and has been used in a wide array of studies
101 (Kalnay et al., 1996; Kistler et al., 2001). This product starts in 1949 and continues to update the
102 time series using the same model and assimilation scheme. The atmospheric model is spectral and
103 uses a spherical grid spacing. The spatial resolution in atmospheric models is commonly specified by
104 "T" followed by a number. R1 has a resolution of T62, (210 km) which indicates spectral triangular
105 truncation at wavenumber 62 with a linear grid. R1 uses 3D-VAR.

106 2.2.2. ECMWF ERA40

107 ERA40 is based on its predecessor ERA15 developed at ECMWF and uses 3D-VAR (Uppala
108 et al., 2005). This system has a truncated Gaussian atmospheric model (T159, N80 nominally)
109 (140 km); these data were re-gridded onto a regularly spaced longitude-latitude grid using a spline
110 interpolation. This system includes a wave model which assimilates satellite altimeter observations,
111 but this does not affect our independent simulations.

112 2.2.3. JMA JRA25

113 JMA25 is the first long-term atmospheric reanalysis produced by JMA (Onogi et al., 2007). It
114 uses the JMA assimilation system and observations from satellites from centers world-wide, includ-
115 ing the National Climatic Data Center (NODC) and ECMWF. The atmospheric model resolution
116 is T106 (125 km) and uses 3D-VAR. Ice concentrations were included using the Special Sensor
117 Microwave Imager (SSM/I) and Scanning Multichannel Microwave Radiometer (SMMR).

118 *2.2.4. NCEP CFSR*

119 The NCEP CFSR is a global coupled system composed of atmosphere, ocean, land, and ice
120 models and begins with the modern satellite era 1979-2010 (v1) (Saha et al., 2010). The atmospheric
121 resolution is 38 km (T382) and uses 3D-Var initialized every 6 hours. Version 2 starts in 2011 and
122 has shown improvement in the product especially in the tropical regions, with increased resolution
123 22 km (T574) (Saha et al., 2014). CFSR uses 3D-VAR with assimilations being updated every
124 6 hours. CFSR is the only reanalysis product that has a dynamic sea ice model. It uses the
125 elastic-viscous model of Hunke & Dukowicz (1997).

126 *2.2.5. ECMWF ERAI*

127 The ECMWF ERAI improved atmospheric model and assimilation system compared to its
128 predecessor ERA40 (Dee et al., 2011). ERAI established the 4D-VAR assimilation scheme used
129 in reanalysis. The atmospheric model is 76 km (T255). This system contains a coupled wave-
130 atmosphere component and the wave model assimilates altimeter observations.

131 *2.2.6. JMA JRA55*

132 JRA55 is the JMA second official release of a reanalysis starting in 1958, when the use of
133 global radiosondes were established (Kobayashi et al., 2015). This product improves many of the
134 aspects for JRA25 by implementing 4D-VAR with variational bias correction for satellite radiances,
135 including a new radiation scheme, and introducing greenhouse gases that vary with time. The
136 atmospheric resolution is 62 km (T319). A notable impact to wave modeling is the inclusion of an
137 embedded parametric model to best capture the intensity of the tropical cyclones using information
138 for the best track database; it captures 95% of the events (Murakami, 2014).

139 *2.2.7. NASA MERRA (v2)*

140 The MERRA (v2) (called MERRA herein) is a NASA reanalysis that uses the Goddard Earth
141 observing system Data assimilation System (GEOS) (Rienecker et al., 2011; Gelaro et al., 2017).
142 One of the original goals of the project (v1) was to simulate the hydrological cycle correctly (Rie-
143 necker et al., 2011). The latest release of the product improves many aspects, including the model,
144 observing system data, radiance assimilation, and the boundary conditions for sea surface temper-
145 ature and sea ice concentration based on Reynolds et al. (2002). The atmospheric resolution is
146 55×70 km and uses 3D-VAR with assimilations being updated every 6 hours.

147 *2.2.8. CIRES R20C*

148 The NOAA Cooperative Institute for Research in Environmental Sciences (CIRES) Climate
149 Diagnostics Center led an effort to produce a reanalysis dataset spanning the entire 20th cen-
150 tury, assimilating only surface observations of air pressure and boundary conditions observed from
151 monthly sea surface temperature and sea ice concentration (Compo et al., 2006, 2011). R20C has
152 been extended to 1851 and has an advantage of not being subject to changes in the quality or
153 quantity of data assimilated in the modern era. This reanalysis applies a Kalman filter for each
154 6-hour analysis pressure field (3D-VAR) with an atmospheric model of 200 km (T62).

155 *2.2.9. ECMWF ERA20C*

156 The ECMWF follows R20C practices and created a reanalysis for the 20th century (Stickler
157 et al., 2014). In addition to atmospheric pressure, surface winds are assimilated into the reanalysis.
158 It includes a coupled land and ocean wave model. The resolution is 125 km (T159) and uses a
159 4D-VAR assimilation scheme which is input approximately at 210 km.

160 *2.2.10. NCAR CFDDA*

161 The National Center for Atmospheric Research (NCAR) Climate Four Dimensional Data Assim-
162 ilation system (CFDDA) established a method to downscale a mesoscale model (Hahmann et al.,
163 2010). NCAR produced a 21-year (1985-2005) reanalysis based on the NCEP Reanalysis 2 (R2)
164 (Kanamitsu et al., 2002). The mesoscale model (MM5) is implemented at 40 km resolution us-
165 ing 4D-VAR. We chose to include this reanalysis to give insights on using downscaling through a
166 mesoscale model. Also, it uses a 4D-VAR instead of the other NCEP products which use 3D-VAR.

167 *2.2.11. RSS CCMP (v2)*

168 Remote Sensing Systems (RSS) produced a cross-calibrated multi-platform (CCMP) gridded
169 surface vector winds at regularly spaced time interval (6 h) (Atlas et al., 2011). Data is combined
170 from 7 radiometer missions, 2 scatterometer missions (QuikSCAT, ASCAT), moored buoys, and
171 atmospheric models using a variational analysis method to produce global maps at 0.25° (27 km).
172 The most recent release (v2) uses updated satellite observations compared to its predecessor (Atlas
173 et al., 2011). We use sea ice concentrations from radiometers produced by Institut Francais pour
174 la Recherche et l'Exploitation de la MER (IFREMER), making the forcing fields completely derived
175 by satellite observations. The ice coverage is produced by using a transfer equation that relates the

176 polarization difference to ice concentration (Kaleschke et al., 2001). The daily sea ice concentrations
 177 have an original spatial resolution of 12.5 km covering both poles. This dataset was used in an
 178 Arctic wave hindcast and captures the daily ice features well (Stopa et al., 2016b).

179 *2.2.12. IFREMER SCT*

180 IFREMER created a merged satellite product consisting of radiometers and scatterometers from
 181 1992-2016 (Bentamy et al., 2016; Desbiolles et al., 2017). This product includes wind vectors from
 182 IFREMER (ERS-1 and ERS-2), NASA (QuikSCAT), and EUMETSAT (ASCAT-A, ASCAT-B),
 183 and radiometers from RSS (SSM/I SSMIS, and WindSat). The use of ancillary data sources such
 184 as radiometer data (SSM/I, SSMIS, WindSat) and ERAI has enabled a blended product available
 185 at spatial resolution and every 6 hours with spatial resolution of 0.25° (27 km) by using optimal
 186 interpolation and kriging methods. Note that data contained in either CCMP or SCT has also been
 187 assimilated into the reanalysis datasets with the exclusion of R20C and ERA20C. Indeed CCMP
 188 and SCT use the same datasets but the geophysical model functions which relate the measured
 189 mean radar cross-section to U10 are different. CCMP uses the RSS GMF's which are expected
 190 to be more accurate for high wind speeds (e.g. Ricciardulli & Wentz, 2015). We use the sea ice
 191 concentration dataset produced by Ifremer as input (like CCMP).

192 *2.3. Model implementation*

193 The wave datasets are generated using WAVEWATCH III version 5.16 (abbreviated WW3
 194 herein). WW3 integrates the spectral wave action equation in space and time, with discretized
 195 wave numbers and directions. Conservative wave processes like propagation, represented by the
 196 local rate of change and spatial and spectral transport terms, are balanced by the nonconservative
 197 sources and sinks. We implement the same global model setup as Raschle & Ardhuin (2013). The
 198 model has a spatial grid of 0.5° in longitude and latitude covering ($78^\circ\text{S}, 80^\circ\text{N}$) and ($0^\circ\text{E}, 360^\circ\text{E}$),
 199 with spectra composed of 24 directions and 32 frequencies exponentially spaced from 0.037 to 0.7
 200 Hz at an increment of 10%. Obstructions such as islands smaller than the spatial resolution are
 201 accounted by apportioning the energy in the x and y-directions (Chawla & Tolman, 2008). The
 202 nonlinear wave-wave interactions are modeled using the discrete interaction approximation (DIA)
 203 of Hasselmann et al. (1985). Dissipation due to bottom friction uses the SHOWEX formulation to
 204 parameterize sandy bottoms, here with a constant sand grain size of 0.2 mm (Ardhuin et al., 2003).
 205 The Ultimate Quickest third order propagation scheme is implemented along with garden sprinkler

reduction (Tolman, 2002). All model simulations are forced with the listed wind fields and sea ice concentrations in Table 1.

We implement physical formulations that describe the wind input and dissipation of Ardhuin et al. (2010). This package of physical parameterizations performs well especially in terms of higher order moments of the wave spectrum and treatment of swell (Stopa et al., 2016a). One major advance when using this package is its treatment of swell which is described by a laminar-to-turbulent boundary within the atmosphere and was formulated and calibrated by tracking swells from synthetic aperture radar (Ardhuin et al., 2009; Stopa et al., 2016c). The wind input is adapted from the Janssen (1991) formulation, with an important reduction of input at high frequencies necessary to achieve a balance with the whitecapping term. The original formulation from Janssen (1991) is written in terms of the wave action $N(k, \theta)$ for each wavenumber (k) and direction (θ)

$$S_{in}(k, \theta) = \beta_{MAX} \frac{\rho_a}{\rho_w} \frac{1}{\kappa^2} e^Z Z^4 \left(\frac{u_*}{C} + z_\alpha \right)^2 \cos^{p_{in}}(\theta - \theta_u) \sigma N(k, \theta) \quad (1)$$

where $\rho_{a,w}$ are the atmosphere and water densities, κ is the von Karman constant, p_{in} is a constant that controls the directional distribution of S_{in} , σ is the wave frequency, z_α is a wave age dependent tuning parameter, u_* is the friction velocity, and Z is a parameterized sea surface roughness. The term β_{MAX} is a non-dimensional growth parameter that controls the wind to wave growth. In this work, we modify β_{MAX} to reduce the overall significant wave height bias. It is expected that other variables such as the roughness length (z_α) or even parameters in the dissipation source term could be modified to reduce the errors associated with different wind forcing.

3. Calibration and Validation

In the following each wind dataset is optimally calibrated and then each 1-year hindcast is compared to the altimeter and buoy observations to establish their performance. Our goal is to establish the optimal β_{MAX} that reduces the global sea state errors for the 0.5° model implementation. There is a distinct seasonality in the H_s ratios (model/altimeter) as shown in Chawla et al. (2013). Therefore we use a 1-year hindcast to avoid any over-fitting that would occur if a particular month or season was used. The year 2001 is used since all datasets overlap during this period, there are 3 altimeter platforms in operation, and it is the middle of the modern reanalysis period from 1979-2016.

233 3.1. Calibration

234 As briefly discussed in the introduction, in Figure 1 there are notable differences of the wind
 235 products. The U10 PDFs have similar shapes and the PDF maximum is within 6 to 8 ms^{-1} (Figure
 236 1a). For upper wind speeds ($\text{U10} > 25 \text{ ms}^{-1}$), there are distinct differences and the maximum U10
 237 ranges from 24 to 43 ms^{-1} . The lower spatial resolution products (ERA40, ERA20C, R1) have less
 238 occurrences of high wind speeds, which is expected since they cannot resolve the fine scale features.
 239 The high resolution mesoscale model implemented by CFDDA has lower wind speeds near the
 240 mean and upper wind speeds relative to the other products and altimeters (Figure 1b). R20C with
 241 its 210 km spatial resolution consistently has higher wind speeds in the range $20 < \text{U10} < 26$
 242 ms^{-1} compared to the altimeters. In Figure 1b, near the U10 average, most datasets are shifted
 243 to the left of the altimeter. The geophysical model function (GMF) relates the measured satellite
 244 normalized radar cross section (NRCS) of the altimeter to estimate U10. When waves are present
 245 this 1-parameter fit can result in an overestimation of U10 (Gourrion et al., 2002). The U10 from
 246 ALT deviates from all other products near the 5th through 30 percentile. It is expected that this
 247 systematic over-estimation of the derived U10 from altimeters at low-wind speeds causes the shift in
 248 the PDF relative to the other datasets. The cause of the overestimated U10 from altimeters under
 249 light wind speeds ($< 4 \text{ ms}^{-1}$) could be due to specular reflection of the nadir-looking altimeter
 250 and/or sea state impact to the radar cross section. Notice that when $\text{U10} > 8 \text{ ms}^{-1}$ CFSR, CCMP,
 251 and SCT more closely match the observations. The same data is plotted in QQ plots in Figure 1c.
 252 It is clear most products have reduced wind speeds relative to the altimeters in the range (3,10)
 253 ms^{-1} and when $\text{U10} > 12 \text{ ms}^{-1}$ the products begin to deviate from each other with the most drastic
 254 deviation when $\text{U10} > 20 \text{ ms}^{-1}$. CFSR and CCMP perform well, with their U10 within 0.5 ms^{-1}
 255 of the altimeter observations even at the 99th percentile.

256 The growth parameter β_{MAX} is arbitrarily set to 1.45 for all hindcasts in Figure 1d,e,f. There
 257 are some consistent features between the U10 and H_s PDFs. The coarser spatial resolution products
 258 (R1, ERA40, JRA25, ERA20C, ERAI) also have lower H_s . In Figure 1d the shapes of the PDFs
 259 are similar and the mean is within [1.5,2.2] m. CFDDA has a higher occurrence of small wave
 260 heights, while R20C has the lowest occurrence of small wave heights when $H_s < 1.5$ m. When
 261 $H_s > 5.6$ m, R20C systematically has the largest probability relative to all other hindcasts. Even
 262 though CCMP and SCT both incorporate data from scatterometers, they use different GMFs, and
 263 these differences are clearly seen in the wave heights. When comparing to the altimeters (Figure

1e), most datasets follow the features seen in the winds and the PDFs are shifted the left of the altimeters close to the average sea states ($1 < H_s < 2.2$ m). We have more confidence in the H_s from altimeters, so most of the forcing wind products might indeed have difficulties in estimating calm wind speeds, which also contributes to the differences observed in the U10 PDFs (Figure 1b). The calm winds located in the tropics are expected to have larger uncertainties (Saha et al., 2014). The QQ plot (Figure 1f) shows a wide range of the wave heights from the hindcasts. So simply using the same β_{MAX} for every input wind dataset results in a wide range of H_s errors. For the highest sea states ($H_s > 10$ m the 99.9 percentile), R1, ERA40, ERAI, ERA20C underestimate H_s and JRA55, CCMP, and R20C overestimate H_s when $\beta_{MAX}=1.45$.

Using CFSR as an example, β_{MAX} is varied and the corresponding H_s PDFs and QQ plots co-located with ALT are given in Figure 2. It is clear that larger values of β_{MAX} result in taller wave heights. Our goal is to optimally determine the value for β_{MAX} where the H_s PDFs output from the wave model and the altimeter observations best align. The optimal β_{MAX} is determined for each dataset by searching the entire space of β_{MAX} , which is typically within [1.0,2.1], with the exception of CFDDA. We require the 50 percentile (P50) and P99 of the significant wave height are well matched between the hindcasts and the altimeters: $(-0.1 \text{ m} < P50, 99_{WW3, H_s} - P50, 99_{ALT, H_s} < 0.1 \text{ m})$ and require that P99 does not underestimate H_s . This second criteria is due to the important engineering applications of capturing the extreme wave heights. In general, we place more emphasis on capturing the largest sea states often at the expense of moderate seas. In this example (Figure 2), the hindcast using $\beta_{MAX}=1.385$ best matches the P50, P99, and the upper wave heights ($H_s > 10$ m). In the QQ plot (Figure 2b) $\beta_{MAX}=1.385$ closely fits the bisector line.

In Figure 3, we objectively adjust β_{MAX} to determine the optimal value to reduce H_s residuals of the P50 and P99. These plots show β_{MAX} (x-axis) versus various percentile differences (WW3-ALT) and the root means square error. The coarser resolution products such as R1, ERA40, ERA20C have optimal performance when β_{MAX} is larger (> 1.7). On the other hand, the higher resolution products such as CFSR, CCMP, and SCT have lower values for β_{MAX} . But in general this is not a rule since R20C with 210 km spatial resolution has an optimal performance when β_{MAX} is close to 1.10. An ideal behavior is when all percentiles intersect with negligible residual; this means the PDFs are well matched for all sea states. Therefore ERA40, CFSR, ERAI, CCMP, and SCT all have good agreement with the altimeters for the majority of the sea states. The only datasets which do not match our criteria of having H_s residuals ± 10 cm are R20C and CFDDA. For

295 R20C the median residual is underestimated by 12 cm and the P99 residual overestimated by 15
 296 cm. For CFDDA, we chose $\beta_{MAX} = 2.55$ because the RMSE has a very subtle minimum. We tested
 297 larger values of β_{MAX} (up to 3.5) to get a better match of the extreme seas, but the PDFs did not
 298 resemble the altimeter observations. Clearly this dataset is not suitable to drive a wave hindcast.
 299 These plots can be used to understand how to calibrate the models for different applications. For
 300 example, to study the average sea states different criteria can be implemented. It is important to
 301 reinforce the fact that these charts are valid for the spatial resolution of 0.5° and applicable for a
 302 global implementation. Models with different spatial resolution and coverage will need refinement
 303 and possible re-calibration.

304 3.2. Validation

305 The optimal β_{MAX} values are given in Table 2 and are chosen from Figure 3. Here we summarize
 306 the overall performance of the 12 1-year hindcasts that use different wind forcing. We compute
 307 standard error metrics: the bias, root mean square error (RMSE), scatter index (SI), and slope
 308 of the linear regression (see Stopa et al. (2016a) for equations). There are clear differences in the
 309 performance of the older reanalysis datasets (R1, ERA40, JR25, and CFDDA) compared to the
 310 recent reanalysis datasets (CFSR, ERAI, JRA55, and MERRA). The older reanalysis (R1, ERA40,
 311 JRA25, CFDDA) have higher RMSEs and SIs of > 0.43 m and $> 15\%$ compared to < 0.41 m
 312 and $< 15\%$ for more recent reanalysis (CFSR, ERAI, JRA55, and MERRA). The 20th century
 313 reanalysis datasets (R20C and ERA20C) perform worse than the other reanalysis datasets. Both
 314 R20C and ERA20C have similar error metrics. R20C underestimates the H_s but has slightly better
 315 match of the linear regression slope. Both of the merged satellite-observation datasets (CCMP and
 316 SCT) perform well with RMSE < 35 cm and SI $< 13\%$.

317 We generate similar error metrics for the extreme sea states ($H_s > 10$ m); the values are provided
 318 in parenthesis in Table 2. The performance of all hindcasts degrade at the extremes. All hindcasts
 319 have H_s RMSEs that exceed 1 m and some have biases that underestimate H_s by at least 1.5 m,
 320 such as R1, CFDDA, R20C, ERA20C. The hindcasts that best capture the largest waves are CFSR,
 321 MERRA, CCMP, and SCT, shown by the RMSEs < 1.5 m and linear regression slopes between
 322 0.88 and 1.14. ERAI is a precise forcing wind field (SI $< 10\%$), but underestimates the largest
 323 heights as reported by others (Rascle & Ardhuin, 2013; Stopa & Cheung, 2014). CFDDA is out of
 324 the reasonable range and significantly underestimates the largest waves.

325 The PDFs and QQ plots are given in Figure 4 after calibration to complement Figure 1. Now
 326 the H_s PDFs (Figure 4a,b) closely resemble each other and the altimeter observations with the
 327 exception of CFDDA. At the extreme sea states the lower resolution products (R1, ERA20C,
 328 ERA40) still have reduced probability relative to the others and altimeter observations. The QQ
 329 plots are relatively close for all products and deviate less than 0.5 m up $H_s=8.4$ m (P99.5). Notice
 330 we calibrated β_{MAX} at P99 and required all products do not underestimate H_s . At the largest
 331 quantile shown (P99.9) the H_s range is about 1 m between products.

332 Often in engineering and oceanographic applications other variables besides H_s , such as the
 333 wave period and direction, are important. We use the buoys from the NDBC network to compare
 334 H_s , average wave periods ($Tm02$)

$$Tm02 = \sqrt{m_0/m_2} \quad (2)$$

335 where $m_i = \int_{0.037}^{0.4} (2\pi f)^i E(f) df$ is a frequency (f) moment of the wave spectrum (E) and the
 336 average wave direction (θ_{avr})

$$\theta_{avr} = \arctan \left(\frac{\int_{0.037}^{0.4} \int_0^{2\pi} \sin(\theta) E(f, \theta) d\theta df}{\int_{0.037}^{0.4} \int_0^{2\pi} \cos(\theta) E(f, \theta) d\theta df} \right). \quad (3)$$

337 We truncate the integration of the buoys at 0.4 Hz since beyond this frequency the data is often
 338 noisy. We use the same frequency range in the wave model output to ensure a fair comparison
 339 between the computed parameters.

340 The results summarized in Table 3. The RMSEs and SIs are given for both the H_s and $Tm02$.
 341 For θ_{avr} the RMSE is reported as well as the normalized standard deviation $NSTD$

$$NSTD = \left(\frac{std(\theta_{avr, hindcast})}{std(\theta_{avr, buoy})} - 1 \right) \times 100 \quad (4)$$

342 where std is the standard deviation and the $NSTD$ is given in a percentage. Note that we are
 343 using circular mathematics for the θ_{avr} error metrics. We see the H_s RMSEs are typically between
 344 0.2 and 0.6 m and the SIs are between 9 and 37%. For $Tm02$ the RMSEs are between 0.7 and 1.7 s
 345 and the SIs are typically between 6 and 20%. Nearly all the hindcasts have θ_{avr} RMSEs of 30° for
 346 the Northeast Pacific and 50° in the Gulf of Mexico. Therefore the directional components of the
 347 wave model need improvement similar to the findings of Stopa et al. (2016a). The θ_{avr} $NSTD$ s of
 348 the hindcasts are typically 0 to 43% less than the buoy observations. This means the directional
 349 components are relatively smooth compared to the observations; this is particularly true for the
 350 Northeast Pacific. In the Northeast Pacific and Gulf of Mexico the hindcasts are performing the

351 worst with the largest H_s and $Tm02$ RMSEs. In the Gulf of Mexico the θ_{avr} RMSEs are large,
 352 and possibly small scale atmospheric features are not well captured by the products. Notice ERAI
 353 has some of the lowest SIs for both H_s and $Tm02$, demonstrating it is a precise forcing wind field.
 354 CFSR systematically has the lowest RMSEs and SIs for $Tm02$. Some other credible forcing fields
 355 are modern reanalyses (CFSR, JRA55, MERRA) and the satellite datasets (CCMP and SCT).

356 The spatial view of the hindcast performances relative to ALT are given in Figures 5 and 6 for
 357 the normalized RMSE (NRMSE) and the SI respectively. These error metrics show the hindcasts'
 358 accuracy and precision respectively. The wave hindcasts are interpolated in space and time to
 359 match the altimeters and the error metrics are computed in 2° bins for each 1-year hindcast. For
 360 the NRMSE (Figure 5), it is clear that R1, R20C, ERA20C, and CFDDA have worse performance
 361 compared to the other products since the NRMSE is often $> 15\%$. It is interesting to note that the
 362 older reanalysis datasets such as ERA40 and JRA25 perform reasonably well once they are properly
 363 calibrated. However, their performance is worse than their successors ERAI and JRA55 respectively.
 364 JRA55 has larger errors in the tropics compared to the other recent hindcasts (CFSR, ERAI, and
 365 MERRA). ERA20C and R20C have similar spatial patterns and clearly have improved performance
 366 in the Northern Hemisphere (NH) compared to the Southern Hemisphere (SH). This is expected
 367 since the majority of the pressure observations were recorded in the NH. CFSR, ERAI, JRA55,
 368 MERRA, CCMP, and SCT all perform well. CCMP has the best performance with approximately
 369 68% of the oceans having a NRMSE $< 8\%$ with a close second to SCT at 65%. CFSR and
 370 MERRA have best performance and have NRSMEs less than 8% for 62 and 58% of the oceans
 371 respectively.

372 The corresponding plots for the SI are given in Figure 6. R1, CFDDA, R20C, and ERA20C have
 373 worse performance than the other hindcasts with $SI > 15\%$. R20C and ERA20C have lower precision
 374 (higher SIs) in the SH. The SIs are less than 10% in the majority of the oceans for CFSR, ERAI,
 375 JRA55, MERRA, CCMP, and SCT. CCMP, SCT, CFSR, and MERRA are the top 4 best forcing
 376 fields with SIs less than 10% for 87, 86, 82, and 79% of the oceans respectively. In general, all wave
 377 hindcasts have larger NRMSEs and SIs that are typically 2-5% higher near the Equator compared to
 378 surrounding regions. In addition, near the ice edge in the Southern Ocean all hindcasts have larger
 379 errors, and these features are more pronounced in the older reanalysis products like R1, ERA40, and
 380 JRA25. Therefore either ice edge location and/or the atmospheric models are performing better in
 381 the more recent reanalysis datasets (CFSR, ERAI, JRA55, MERRA).

382 4. Comparison and extremes

383 To assess the different hindcasts we compute the average and standard deviation of different
 384 statistics from the ensemble (Figure 7). In this analysis we remove CFDDA since this hindcast was
 385 not in the reasonable range compared to the observations. The median in Figure 7a,b shows the
 386 SH has larger sea states than the NH. More importantly, the variability shown by the standard
 387 deviation of these 11 hindcasts is typically less than 30 cm globally. In fact 68%, 88%, and 97%
 388 of the ocean has standard deviation less than 10, 15, and 20 cm respectively. Note that in Pacific
 389 near the Equator there is a region with standard deviations of 10 to 20 cm and the H_s P50 is only
 390 1.5 m. So this region has a large relative variability (approx. 15%) compared to the extra-tropics
 391 ($< 5\%$). For H_s P95 (Figure 7c,d), the NH and SH now have similar magnitudes with maximum
 392 in the Indian Ocean sector of the Southern Ocean. The magnitude of H_s P95 is relatively smooth
 393 and the standard deviation is mostly less than 20 cm. Specifically 64%, 90%, and 97% of the ocean
 394 has standard deviations less than 20, 30, and 40 cm respectively. The maximum H_s in Figure
 395 7e,f does not have a smooth pattern, and impact from individual storms can be identified. The
 396 standard deviation shows particular events can have very large H_s differences exceeding 2.5 m. In
 397 the lower latitudes, the standard deviations of the hindcasts are less than 50 cm with the exception
 398 of tropical cyclone regions that are most notable in the Western Pacific and Atlantic. Most of the
 399 variability is in the extra tropics, and it is common to have standard deviations greater than 1 m.
 400 The maximum H_s differences come from variations in the magnitude of the forcing wind fields or
 401 space-time deviations of the storm locations.

402 In short, all hindcasts reproduce the average sea state conditions within 10 cm of each other;
 403 even the H_s P95 is well matched between hindcasts. The largest sea states have greater variability
 404 between the hindcasts, and these differences are quantified by calculating the occurrence of $H_s > 10$
 405 m (based on hourly data). The results are presented in Figure 8. It is clear that the extra-tropics
 406 have the strongest and most persistent storms. Tropical cyclones can indeed breach this threshold,
 407 but their occurrence is low compared to extra-tropical events. R1, ERA40, and JRA25 have similar
 408 patterns. JRA25 has slightly larger waves in both hemispheres. CFDDA is not applicable to capture
 409 these high sea states, and most of the ocean has $H_s < 10$ m. CFSR, ERAI, JRA55, and MERRA
 410 have similar spatial patterns. ERAI has the least energy at high sea states, and it is known that
 411 ERAI underestimates these conditions (Stopa & Cheung, 2014). In the SH, CFSR has reduced
 412 seas compared to JRA55 and MERRA. In the NH, MERRA and CFSR have similar occurrence

413 of $H_s > 10$ m, but JRA55 has less occurrences of elevated seas. R20C and ERA20C have similar
 414 patterns; however R20C has more occurrences of elevated seas in the SH especially in the Indian
 415 Ocean; and perhaps this is too high with respect to the other hindcasts. CCMP and SCT have
 416 nearly the same pattern with slightly more wave activity in SCT. Notice the consistency between
 417 the products produced by the same centers: NCEP (R1, CSFSR, R20C), ECWMF (ERA40, ERAI,
 418 ERA20C), and JMA (JRA25, JRA55). The recently released products have higher occurrence of
 419 elevated wave heights ($H_s > 10$ m), which is due to the fact that the spatial resolution increases,
 420 physical parameterizations improve, and satellite observations at extremes improve.

421 It is clear that the bulk statistics are different for the upper wave heights so two particular storms
 422 are analyzed to further highlight the differences. The largest altimeter record for 2001 ($H_s > 16$ m)
 423 was recorded in a Southern Ocean extra-tropical storm by GFO. This storm from April 10 to April
 424 13 traveled south of Australia in the Southern Ocean (Figure 9a). As the storm intensified on April
 425 10 at 17:00, the spatial patterns of the H_s exceeding 9 m are different for each hindcast (Figure
 426 9c). ERA40 has the smallest spatial coverage of $H_s > 9$ m at 1.6×10^5 km², while most hindcasts
 427 (JRA25, CFSR, ERAI, R20C, ERA20C, and SCT) have areas with $H_s > 9$ m within $2.8 - 3.8 \times 10^5$
 428 km². R1, JR55, MERRA, and CCMP have enhanced sea states with regions of $H_s > 9$ m exceeding
 429 4×10^5 km² and H_s larger than 12 m. Notice that nearly all hindcasts have the storm in nearly
 430 the same position. The exception is R1, which places the storm slightly ahead of the others.

431 When the storm is nearly at its peak intensity, GFO crosses the storm center on April 12 at
 432 03:45. The storm contours are given in Figure 9d and all hindcasts have the storm in the same
 433 position with the exception of R1. The spatial coverage of $H_s > 9$ m between hindcasts varies by
 434 7×10^5 km² with maximum being R20C and minimum ERA40. The altimeter observations in
 435 Figure 9b give insight to which models best capture the maximum H_s and spatial extent of the
 436 storm waves. It is confirmed that storm location in R1 is incorrect. Ignoring CFDDA and R1,
 437 the hindcasts have the maximum H_s ranging from 12 to 18 m for this event. JRA55 captures
 438 the maximum of the storm very well with only a small displacement to the South. MERRA is
 439 the only hindcast that overestimates the peak of the event by 1.3 m. In addition JRA25, R20C,
 440 ERA20C perform well and underestimate the altimeter H_s of 16.4 m by 50 cm. ERAI, CCMP,
 441 and SCT moderately underestimate the peak H_s by 1-2 m while CFSR and ERA40 unreasonably
 442 underestimates the peak H_s by 3 m. Towards the end of the event, on April 12 at 22:00, there is
 443 large variability in the spatial coverage of $H_s > 9$ m that exceeds 6×10^6 km² between hindcasts

444 (Figure 9e). Some hindcasts fall below the H_s threshold of 9 m and are not plotted. The time
 445 evolution of the maximum H_s and area of $H_s > 9$ m are given in Figure 9f,g. It is clear that towards
 446 the end of the storm there is more variability in the spatial distribution of the largest waves. Also
 447 notice that the hindcasts have maximum H_s that vary from 4 to 8 m for the duration of the event.

448 In Figure 7f it is clear that regions affected by tropical cyclones have larger variability with
 449 H_s standard deviations exceeding 2 m. We pick the tropical cyclone Utor in the Western Pacific
 450 near the Philippines that occurred July 1-5 to demonstrate the large variability of the hindcasts
 451 under extreme tropical cyclone wind forcing. This event is clearly seen in Figure 7c. Utor grazed
 452 the island of Luzon in the Philippines and then made landfall in Southeast China on July 6. The
 453 cyclone overview is given in Figure 10a. There was a TPX pass that intersected the storm center on
 454 July 3 07:11. The spatial distribution of the $H_s > 8$ m on July 2 is similar for the various hindcasts
 455 and the $H_s = 8$ m contours have a "C" pattern (Figure 10c). Note that R1 has the storm in different
 456 location relative to the other hindcasts, similar to the last case.

457 When TPX crosses the storm on July 3 in Figure 10b there is a large range of H_s profiles.
 458 MERRA overestimates H_s and it is confirmed that the location of Utor in R1 is mis-located com-
 459 pared to the altimeter observations. In this case, ERAI best matches the TPX H_s but with an
 460 underestimation of 1 m. All other hindcasts (ERA40, JRA25, CFSR, JRA55, CFDDA, R20C,
 461 ERA20C, CCMP, and SCT) underestimate the maximum H_s of the event ($H_s = 11.2$ m) by 2 to
 462 5 m. The positions of the storm in ERA40, CCMP, ERAI, and MERRA are approximately correct
 463 since the H_s profiles follow the TPX observations. The spatial coverage of $H_s > 8$ m varies greatly
 464 between products 10×10^5 km² (Figure 10c,d,e,g). Towards the end of the event and as the storm
 465 moves into the South China Sea, the spatial patterns of $H_s > 8$ m vary by 3×10^5 km². Figure
 466 10f,g shows the time series of the maximum H_s and storm area with $H_s > 8$ m. It is clear that
 467 the maximum H_s has a large variability between products. Of course some products like R20C
 468 and ERA20C are not specifically designed to capture the small-scale features of tropical cyclones.
 469 This particular example shows that the range in H_s can be 8 m between the hindcasts. There-
 470 fore extreme caution should be used when using these hindcasts to understand extreme sea states,
 471 especially for tropical cyclones.

5. Discussion and Recommendations

In this work we calibrated 12 different wind products by adjusting the β_{MAX} parameter that describes the wind to wave growth in the Janssen (1991) formulation. We demonstrate that modifying β_{MAX} reduces errors in the wave field. This is due to the fact that each wind product has different characteristics. This exercise was performed on a 0.5° global grid, and we used altimeter observations as reference for the calibration. Then we compare the hindcasts to NDBC moored buoys to assess H_s , $Tm02$, and θ_{avr} . Our procedure can be adapted to regional domains with different resolutions. However, one should take caution when applying this approach, especially with a sufficiently small domain, because β_{MAX} could be incorrectly compensating for missing or improper model parameterizations.

Our criteria was to best match the H_s PDFs, and we ensured the largest sea states >P99 are not underestimated. We specifically summarize the advantages and disadvantages of each hindcast in Table 4 and here we generalize the conclusions. After calibration, even the older reanalysis datasets, such as R1, ERA40, and JRA25, perform well with respect to bulk statistics. Our results clearly demonstrate that the more recent reanalysis wind fields from CFSR, ERAI, JRA55, and MERRA are better forcing wind fields for wave hindcasting compared to their predecessors. The NCEP 4D-VAR reanalysis that uses a mesoscale model, CFDDA, is not suitable for wave hindcasting. This wind forcing cannot capture the high sea states; there is an extreme underestimation. The 20th century reanalysis datasets R20C and ERA20C have similar performance. These hindcasts do not perform as well as the higher resolution products and have less fidelity than the other hindcasts. However, it is important to note that they capture the magnitude of the extreme events especially in the extra tropics. R20C and ERA20C poorly capture tropical cyclones. The hindcasts driven by satellite observations (CCMP and SCT) perform well and are as good if not better than the reanalysis products. However, their 6-hour time step might not be sufficient for some cases, such as rapidly intensifying storms.

The buoy comparison gives an independent check of the calibrated wave hindcasts. The H_s error metrics between the buoys and altimeters are similar; however, regional areas such as the Northeast Pacific and Gulf of Mexico have larger errors. The RMSEs for the $Tm02$ are typically 1 s and exceed 1.6 s in the Gulf of Mexico. All wave hindcasts have similar performance for average wave directions, which is most likely due to the same model source term parameterization and implementation of the DIA. In the Gulf of Mexico the θ_{avr} are poor with RMSEs of 50° , suggesting

503 model improvements are needed to better capture the directionality of the wave field.

504 All hindcasts have similar average sea states (P50), and the variability between hindcasts is
505 negligible ($<5\%$). Even up to the 95th percentile, the variability between hindcasts is typically
506 less than 10%. The hindcasts deviate only at the largest sea states. Extra-tropical storms are well
507 captured by the hindcasts. However, the variability for the largest events and the occurrence of
508 these events varies greatly between products. For the example storms, the maximum H_s can exceed
509 6 m for a large extra-tropical event and vary by 8 m for a tropical cyclone. For practical applications
510 it is important to understand that each forcing wind field will give very different results for high
511 sea states. Using an ensemble approach such as this to study extreme events will help quantify
512 some of the uncertainty. In general it is clear that tropical cyclones are not well captured. Some of
513 the reanalysis products are able to capture the tropical events better than others (Murakami, 2014;
514 Hodges et al., 2017).

515 For wave hindcasting we recommend CFSR, ERAI, JRA55, MERRA, CCMP, and SCT. For
516 extreme waves CFSR, JRA55, MERRA, CCMP, and SCT perform well in terms of bulk statistics.
517 However, the case studies revealed that CFSR underestimated both of the peak H_s events by 2-3
518 meters. On the other hand, ERAI has the storm in the correct position, but maximum H_s was
519 underestimated typically by 1 m. ERAI reanalysis is one of the most precise forcing fields and the
520 SIs from wave parameters are typically the lowest. JRA55 matches the extreme waves very well
521 and is expected to better capture tropical cyclones since they are blended into the product through
522 use of a parametric model Kobayashi et al. (2015); Murakami (2014). MERRA overestimates the
523 largest waves. Of course β_{MAX} can be reduced, but this affects the entire H_s PDF (see Figure 3).
524 A $\beta_{MAX}=1.45$ matches the peak H_s of 16.4 and 11.1 m for the extra and tropical cases studies,
525 but the overall error metrics degraded and a global underestimation was observed (not shown).
526 Otherwise most of the hindcasts underestimate the extreme sea states.

527 For climate studies, the consistency of the products in time is key, and this is a topic of future
528 work. Now with properly calibrated hindcasts this task can be performed more diligently. In
529 particular, R20C and ERA20C might have the advantage of being less affected by changes in
530 the quantity and quality of the assimilated data. Another critical point is the need for continual
531 observations from scatterometers and radiometers, which provide a tremendous resource for the
532 community. As the reanalysis products continually improve, there is a need to assess their ability
533 to reproduce the wave field through hindcasts. Additional and improved measurements of the winds

534 and increased spatial resolution will provide further insights and explanations of regions with large
535 uncertainties especially, for high sea states.

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541 can be obtained from <ftp.ifremer.fr/ifremer/cersat/products/swath/altimeters/waves/>. The IFRE-
542 MER/CERSAT SSMI daily ice concentrations are available from <ftp.ifremer.fr/ifremer/cersat/>.
543 The NDBC buoy data can be accessed from www.ndbc.noaa.gov/. The R1, JRA25, ERA40, CFSR,
544 ERAI, JRA55, and CFDDA wind fields and ice concentrations can be obtained from rda.ucar.edu.
545 MERRAv2 wind fields and ice concentration can be obtained from [gmao.gsfc.nasa.gov/reanalysis/MERRA-](http://gmao.gsfc.nasa.gov/reanalysis/MERRA-2/)
546 [2/](http://gmao.gsfc.nasa.gov/reanalysis/MERRA-2/). CCMPv2 is available via Remote Sensing Systems <ftp2.remss.com/ccmp/>. The Ifremer blended
547 product of satellite wind observations (SCT) is available ftp.ifremer.fr/IFREMER_LOPS_blended_wind/longterm_analysis

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Table 1: Summary of wind datasets used to generate wave hindcasts in this study.

Name	Institution	Spatial Resolution	Time reso- lution	Period	Assimilation	Ice	References
R1	NCEP	$1.875^\circ \times 1.875^\circ$	6 h	1948-present	3D-VAR	Yes	Kalnay et al. (1996)
CFSR	NCEP	$0.3^\circ \times 0.3^\circ$ (v1) $0.2^\circ \times 0.2^\circ$ (v2)	1 h	1979-present	3D-VAR	Yes	Saha et al. (2010, 2014)
R20C	NCEP	$1.875^\circ \times 1.875^\circ$	3 h	1851-present	Kalman Fil- ter	Yes	Compo et al. (2011)
ERA40	ECMWF	$1.125^\circ \times 1.125^\circ$	6 h	1957-2002	3D-VAR	Yes	Uppala et al. (2005)
ERA1	ECMWF	$0.75^\circ \times 0.75^\circ$	6 h	1979-present	4D-VAR	Yes	Dee et al. (2011)
ERA20C	ECMWF	$1.125^\circ \times 1.125^\circ$	6 h	1900-2011	4D-VAR	Yes	Stickler et al. (2014)
JRA25	JMA	$1.125^\circ \times 1.125^\circ$	6 h	1979-2014	3D-VAR	Yes	Onogi et al. (2007)
JRA55	JMA	$0.5625^\circ \times 0.5625^\circ$	3 h	1958-present	4D-VAR	Yes	Kobayashi et al. (2015)
MERRA	NASA	$0.5^\circ \times 0.625^\circ$ (v2)	1 h	1980-present	3D-VAR	Yes	Molod et al. (2015)
CFDDA	NCAR	$0.4^\circ \times 0.4^\circ$	1 h	1985-2005	4D-VAR	No: use R1	Rife et al. (2010); Rife et al. (2014)
CCMP	RSS	$0.25^\circ \times 0.25^\circ$	6 h	1987-present	Scat/Rad	No: use SSMI*	Atlas et al. (2011)
SCT	IFREMER	$0.25^\circ \times 0.25^\circ$	6 h	1993-present	Scat	No: use SSMI*	Bentamy et al. (2016)

Table 2: Error metrics comparing 12 hindcasts with altimeter H_s for all sea states and only when $H_s > 10$ m (values in parenthesis) for 2001. The number of altimeter observations is 10767248 and 8850 for all observations and $H_s > 10$ m respectively. The β_{MAX} given in the second column is the calibrated value used for the hindcast.

Name	β_{MAX}	Bias (m)	RMSE (m)	SI (%)	Lin. Slope
R1	1.750	-0.05 (-1.94)	0.64 (2.62)	23.85 (15.81)	0.91 (0.55)
ERA40	2.050	+0.00 (-1.08)	0.43 (1.57)	15.96 (10.16)	0.97 (0.78)
JRA25	1.500	-0.05 (-1.11)	0.49 (2.05)	18.22 (15.44)	0.95 (0.81)
CFSR	1.385	+0.01 (-0.42)	0.35 (1.19)	13.15 (9.98)	0.95 (0.88)
ERA1	1.660	-0.02 (-0.91)	0.38 (1.37)	14.13 (9.14)	0.98 (0.69)
JRA55	1.215	-0.06 (-0.49)	0.41 (1.27)	15.26 (10.46)	0.98 (0.86)
MERRA	1.630	-0.06 (+0.24)	0.36 (1.22)	13.26 (10.72)	0.97 (1.06)
CFDDA	2.550	-0.09 (-3.30)	0.87 (3.96)	32.05 (19.60)	0.73 (0.73)
R20C	1.100	-0.09 (-1.54)	0.66 (2.67)	24.48 (19.54)	0.94 (0.65)
ERA20C	1.710	-0.00 (-2.52)	0.68 (3.46)	25.36 (21.27)	0.89 (0.50)
CCMP	1.300	-0.06 (+0.33)	0.33 (1.30)	12.20 (11.29)	0.95 (1.14)
SCT	1.490	-0.04 (+0.10)	0.35 (1.48)	12.95 (13.26)	0.95 (1.14)

Table 3: H_s , $Tm02$, and θ_{avr} error metrics comparing 12 hindcasts with buoy observations in different regions: Hawaii (HAW), North Pacific (NoP), Northeast Pacific (NEP), Gulf of Mexico (GoM), and the Northwest Atlantic (NWA). The RMSEs are the first value in each cell and the values in the parentheses are the SIs for H_s and $Tm02$ and the $NSTD$ for θ_{avr} given as a percentage. The number of data pairs (denoted by N) is given in the third row.

Name	H_s (m)					$Tm02$ (s)					θ_{avr} (deg)	
	HAW	NoP	NEP	GoM	NWA	HAW	NoP	NEP	GoM	NWA	NEP	GoM
N	34047	19683	134589	37018	31022	34047	19683	134589	37018	31022	8639	37018
R1	0.39(13)	0.78(25)	0.68(29)	0.64(37)	0.45(25)	0.97(9)	0.99(11)	1.61(19)	1.74(19)	1.03(12)	30(-41)	53(0)
ERA40	0.23(10)	0.38(12)	0.59(24)	0.58(31)	0.29(15)	0.84(7)	0.84(6)	1.49(19)	1.75(17)	1.05(9)	31(-40)	53(1)
JRA25	0.29(9)	0.47(15)	0.56(24)	0.58(31)	0.31(17)	0.76(7)	0.77(7)	1.37(16)	1.74(18)	0.89(9)	32(-27)	52(-0)
CFSR	0.27(11)	0.36(12)	0.54(23)	0.55(30)	0.29(16)	0.71(8)	0.69(6)	1.34(15)	1.60(17)	0.82(8)	32(-23)	52(-1)
ERA1	0.27(9)	0.43(14)	0.57(24)	0.60(33)	0.31(15)	0.81(6)	0.80(7)	1.36(17)	1.77(17)	1.01(9)	31(-36)	51(4)
JRA55	0.39(10)	0.44(14)	0.56(23)	0.62(34)	0.33(17)	0.82(7)	0.72(7)	1.42(16)	1.74(18)	0.98(9)	32(-24)	51(4)
MERRA	0.35(11)	0.41(13)	0.55(23)	0.58(31)	0.31(16)	0.84(8)	0.80(6)	1.42(16)	1.74(17)	0.98(8)	32(-28)	53(-0)
CFDDA	0.53(19)	1.29(37)	0.89(36)	0.69(41)	0.50(23)	0.87(10)	1.91(20)	2.06(23)	1.51(19)	0.82(10)	33(-2)	54(-10)
R20C	0.40(13)	0.65(20)	0.60(26)	0.56(31)	0.48(25)	0.93(9)	0.84(10)	1.58(20)	1.57(18)	1.05(13)	30(-43)	59(-7)
ERA20C	0.29(12)	0.59(19)	0.61(27)	0.55(30)	0.40(22)	0.83(8)	0.89(9)	1.64(19)	1.61(17)	1.03(11)	28(-42)	56(-6)
CCMP	0.26(10)	0.40(12)	0.54(23)	0.55(30)	0.30(15)	0.76(8)	0.81(6)	1.43(17)	1.66(17)	0.97(8)	34(-17)	52(0)
SCT	0.22(9)	0.40(11)	0.56(23)	0.56(30)	0.33(18)	0.72(7)	0.87(6)	1.45(18)	1.68(17)	0.96(10)	34(-19)	53(-1)

Table 4: Summary: qualitative wave hindcast performances using different forcing fields.

Name	Advantages	Disadvantages
	Static Reanalyzes	
ERA40	position of storms is accurate; performs the best for a 1st generation reanalysis;	course resolution; underestimates extremes
JRA25	position of storms is accurate;	underestimates extremes
CFDDA	high resolution; NCEP's only 4D-Var	strongly underestimates extremes; poor performance inaccurate for wave hindcasting
	Active Reanalyzes	
R1	long time series; no model or assimilation changes to reanalysis	course resolution; position of storms is incorrect; worst accuracy and precision
CFSR	high resolution; 1-hour time step; captures extremes; best performance of $Tm02$	imprecise; storm location can be inaccurate; inconsistent between v1 and v2;
ERA1	highly precise (lowest SIs); position of storms is accurate	underestimates extremes; 6 h time step can miss important events
JRA55	long time series; captures extremes; incorporation of tropical cyclones	underestimates peaks of extremes; tropics have reduced performance
MERRA	captures extremes; 1-hour time step; continual efforts to improve;	overestimates peaks of extremes
	20th-century Reanalyzes	
R20C ERA20C	+100-yr time series; captures overall climate variability; less sensitive to changes of the data assimilated; captures extra-tropical extremes	R20C overestimates extra-tropical storms; coarse resolution; 6 h time step can miss important events; tropical storms poorly captured; reduced accuracy and precision; worse performance in Southern Hemisphere
	Satellite Wind Fields	
CCMP SCT	lowest H_s RMSEs; high spatial resolution; independent of a model; captures extremes well	shorter time series; interpolation and 6 h time step can create unphysical storm positions and miss important events

Figure 2: H_s PDFs (a) and QQ (b) plots created by modifying the wind to wave growth parameter β_{MAX} and using the CFSR winds as input. The altimeter observations in black are given for reference in (a).

Figure 3: Calibration of the wind datasets based on modifying β_{MAX} and comparing to altimeter H_s . The green line with squares is the P10 (WW3-ALT), the blue line with circles is the median (P50), the red line with triangles is the P99 (WW3-ALT), and the magenta dashed line with diamonds is the root mean square error. The chosen β_{MAX} value is specified by the vertical black line.

Figure 4: H_s PDFs (a,b) and QQ plots (c) for 12 wind datasets (color) using an optimal value for β_{MAX} and comparing to the altimeter observations (black in b). The β_{MAX} was chosen by reducing the differences in the P50 and P99 and ensuring P99 is not underestimated.

Figure 5: The normalized root mean square error of the significant wave height using the satellite altimeters as reference for 2001 in 2° bins. The percentage of oceans that have a NRMSE $< 8\%$ is given for each hindcast.

Figure 6: The scatter index (SI) of the significant wave height using the satellite altimeters as reference for 2001 in 2° bins. The percentage of oceans that have a SI < 10% is given for each hindcast.

Figure 7: The average (a,c,e) and standard deviation (b,d,f) for different H_s percentiles (P50 and P95) and the maximum for 2001 using the 11 different hindcasts excluding CFDDA. Colors denote values are in meters. Panel (a) shows the NDBC buoy locations in five regions: Hawaii (HAW), North Pacific (NoP), Northeast Pacific (NEP), Gulf of Mexico (GoM), and the Northwest Atlantic (NWA).

Figure 8: The occurrence the number of events with H_s larger than 10 m for 2001. This is based on hourly output from the hindcasts.

Figure 9: Extra-tropical storm in the Southern Ocean from April 10 to 13 2001. a) shows the storm track with H_s taken from the MERRA driven wave hindcast. Three representative time periods are highlighted on April 10 at 1200, April 12 at 0400, and April 12 at 2200. The contours represent $H_s=9$ m using the MERRA-driven wave hindcast. The altimeter aboard GFO intersects the storm center on April 12 at 0345. b) shows the GFO altimeter transect and the 12 other wave hindcasts. c,d,e) show the contours with $H_s=9$ m for the representative phases of the storm. f) shows the maximum H_s for the different hindcasts and g shows the area of the storm with $H_s > 9$ m.

Figure 10: Tropical cyclone Utor in the Western Pacific Ocean from July 1 to 5 2001. a) shows the storm track with H_s taken from the MERRA driven wave hindcast. Three representative time periods are highlighted on July 2 at 0700, July 3 at 0700, and July 4 at 1300. The contours represent $H_s=8$ m using the MERRA-driven wave hindcast. The altimeter aboard TPX intersects the storm center on July 3 at 0711. b) shows the TPX altimeter transect and the 12 other wave hindcasts. c,d,e) show the contours with $H_s=8$ m for the representative phases of the storm. f) shows the maximum H_s for the different hindcasts and g) shows the area of the storm with $H_s > 8$ m.